Scaling Probabilistic Soft Logic for Entity Resolution

Eriq Augustine
University of California, Santa Cruz
1156 High St
Santa Cruz, CA 95064
eaugusti@ucsc.edu

Nikhil Kini
University of California, Santa Cruz
1156 High St
Santa Cruz, CA 95064
nkini@ucsc.edu

1 Introduction

Statistical Relational Learning (SRL) allows for modeling richly structured data and is a natural candidate to solve entity resolution (ER) problems. One such SRL framework that is well suited to this task is Probabilistic Soft Logic (PSL). PSL is fast amongst SRL frameworks and scales linearly with the number of ground rules infered over Bach et al. (2015).

However because of the complete nature of ER tasks, the number of ground rules is often polynomial in the number of entities to be resolved. Doing a cross product over all entities to find entities that are the same is a natural and costly step in an ER problem. The huge number of ground rules makes it difficult to process a dataset on a single machine due to lack of memory. The inference algorithm in PSL, ADMM, already uses consensus optimization, which lends itself well to parallelization.

However, distributing the dataset across computers requires a non-trivial partitioning of data that balances the size of the partitions and preserves the relational edges in the data. Blocking is a technique used in ER to restrict the number of comparisons to make based on some shared attribute or similarity metric.

In this paper we study the scalability of PSL in an ER setting, compare data partitioning/clustering techniques such as standard and adaptive blocking, and provide a distributed implementation of PSL.

2 Background

2.1 Entity Resolution

Entity resolution is the task of resolving different mentions of the same underlying real-world entity. For instance, in the field of academic citations, each citation that occurs at the end of the publication contains a mention of authors. Across several publications, different citations to the same publication correspond to the different mentions of the same entity – the publication being cited. The problem was originally defined in 1959 (Newcombe et al. (1959)) under the title of ‘record linkage’. Entity resolution, especially bibliographic entity resolution, naturally lends itself to statistical relational learning, when there are multiple types of entities to resolve and there is relational information inherent in the data, because we can use collective entity resolution. Bhattacharya and Getoor (2007) talk about this in great detail.

The two main challenges in entity resolution are that of noise in the records, and ambiguities in the attributes. With the size of datasets growing since then, we are faced with another problem, that of scaling. Entity Resolution (ER) is commonly modeled as a binary classification problem, comparing pairs of references and classifying them as being either the same or different entities. In such a setting, comparing every pair of references quickly becomes infeasible as the number of references grows. Blocking methods are used to efficiently select a subset of the pairs such that the discarded pairs are highly dissimilar and hence unlikely to be a match.

31st Conference on Neural Information Processing Systems (NIPS 2017), Long Beach, CA, USA.

2.2 Blocking

Blocking is the term used to describe partitioning the data into subsets, called 'blocks', such that the number of comparisons is limited to pairs of references within a block. In other words, a computationally cheap heuristic is used for preprocessing a set of potential matches. For example, suppose the entity resolution problem is to resolve academic publications in two databases. Rather than comparing every record in database 1 with every record in database 2, one can compare only those records for which the year of publication matches. Here, a block consists of all publications with the same year of publication, and the year attribute is known as the block key. Figure 5 shows how a simple blocking heuristic can drastically reduce the number of required comparisons. However, blocking introduces a trade-off between recall and compression. (1 - recall) is the cost of blocking, because blocking can result in references to the same entity never getting matched. Compression, also known as reduction ratio in ER, is the percentage of comparisons saved due to blocking, the benefit of blocking. A blocking method with high recall and high compression is to be preferred.

Several schemes for blocking have been proposed in the past: Standard blocking Jaro (1989) blocks references based on their sharing some chosen key, iterative blocking Whang et al. (2009) and canopies McCallum et al. (2000), and adaptive blocking Bilenko et al. (2006) which learns a blocking function dependent on the features. Blocking is very domain dependent, and not all kinds of blocking will perform well with all kinds of datasets.

2.3 Probabilistic soft logic

Probabilistic soft logic (PSL) is a statistical relational learning framework that allows modeling using first-order logic syntax that encodes the data with hinge-loss Markov Random ields, a probabilistic graphical model that offers scalable MAP inference Bach et al. (2015). PSL makes writing models easy for richly structured data through the use of the intuitive first-order logic syntax, and the convex optimization objective makes it particularly appealing to large relational problems.

2.4 ADMM

The MAP inference algorithm in PSL uses consensus optimization, a distributed optimization technique using the Alternating Direction Method of Multipliers (ADMM). ADMM is an Augmented Lagrangian method that solves the problem:

$$minimize\ f(x) + g(z)$$
$$subject\ to\ Ax + Bz = c$$

with convex functions f and g, variables $x \in R^p$ and $z \in R^q$ and constants $A \in R^{r \times p}$, $B \in R^{r \times q}$, and $c \in R^r$.

ADMM was introduced as an efficient convex optimization technique by Glowinski and Marroco (1975) and Gabay and Mercier (1976), and popularized recently as being well suited to distributed convex optimization by Boyd et al. (2011).

3 Approach

3.1 Distribution

ADMM is already a consensus optimization that decomposes the problem into independent subproblems. Now we will just choose subproblems to distribute across machines. By doing this, we only have to ground out the terms that take part in the relevant subproblems. We can utilize the blocks to define the provide sets of fairly independent subproblems. We we block, we are making the assumption that no entities across blocks can match. Therefore, on each node we only need to consider subproblems that are covered by the blocks on that node.

We use a master/worker architecture with a single master node governing an unspecified number of worker nodes. The master is responsible for allocating blocks to workers, holding the consensus values for the entire problem, and calculating new consensus values. The workers are responsible for grounding out all required ground rules, generating optimization terms, and doing the actual ADMM calculations. All workers will further sub-divide the work to all available cores.

We first transmit the blocks to each worker. The workers will then use the blocks and ground out all ground rules required for their partition of the data. The ground rules are then converted to optimization terms and variables. Each term contains a local copy of each variable used in the optimization terms. Each local copy has a reference back to a global copy of that variable. For example, if we had the optimization terms: $A + B = C$ and $Z + A = Y$. Then the local copies of A in both terms will refer to the same global variable.

After terms are generated, the workers will report back to the master with a list of all the global variables it uses. The master keeps track of all global variables used by all workers as well as a mapping of which workers use which variables. This mapping is used to transmit consensus updates back to each worker.

Now the master will begin iterations of ADMM. It begins with telling the workers to start an iteration of ADMM. This is where most of the computationally intensive work takes place. The workers update their Lagrange values, minimizes each objective term, and calculates values that contribute to the new consensus values (referred to as consensus partials). After a worker completes its work, it transmits the consensus partials to the master. The master aggregates all the partials and computes the new consensus values and dual residual. The master then transmits the new consensus values to the workers. The workers uses these new consensus values to calculate primal residual partials and transmit these values back to the master. The master then aggregates the primal residual partials and uses the dual and primal partials to check for convergence. If no convergence has been reached (and the maximum number of iterations has not been reached), then the master will initiate another iteration of ADMM. Otherwise, the master will tell the workers to shutdown and the master will commit the final consensus values to its database.

Appendix A has several figures that may be useful in understanding the distributed ADMM implementation. Figure 6 shows the network control flow between the master and workers. Figure 7 shows the location of critical pieces of data in a standalone ADMM system. Figure 8 shows the location of critical pieces of data in our distributed ADMM system.

3.1.1 Overlapping Subproblems

In the case where entities can take part in multiple blocks or there are rules in the model that are not fully restricted by the blocking predicates, it is possible that identical terms are grounded on multiple nodes. This makes the Markov random field solved by the distributed case slightly different than the Markov random field solved in the standalone case. Each instance of the identical terms will be minimized with respects to the other terms on that node. Then the variables in each term will be synchronized to a consensus value at the beginning of each ADMM iteration. It is possible to merge these identical instances, but would require significant network and processing overhead. To keep our implementation efficient and fast, we decided to allow the distributed case to solve the related Markov random field instead of the exact one solved by the standalone case.

4 Experiments

4.1 Distribution

To test the results of our distributed ADMM implementation in isolation without the complexity of a real-world entity resolution problem, we constructed a very simple entity resolution problem with accompanying data generator. The goal of these experiments on synthetic data are to ensure that the same solution is reached regardless of the number of workers, examine memory usage under ideal blocking conditions, and examine runtime under ideal blocking conditions. For these experiments, we will be interested in four primary statistics:

- **Grounding Time** – Grounding is typically the most costly single operation, sometimes taking more time than all other tasks combined. By blocking and then distributing those blocks, we are effectively diluting the number of ground rules across machines. The reduced number of ground rules per machine should also translate into less time spent grounding overall.

- **Term Generation Time** – The time it takes to generate optimization terms is directly related to the number of ground rules and the number of variables in each ground rule.
- **Inference Time** – The time it takes the actual ADMM inference to complete. The distributed ADMM includes network overhead in its inference time.
- **Number of Ground Rules** – The number of ground rules (which is also the number of optimization terms) is the primary cause of memory issues. Reducing the number of ground rules per machine allows us to solve larger problems that could previously not be held in memory.

4.1.1 Model

This simple problem is trying to identity if two person references actually refer to the same person.

Our model contains the following predicates:

- **Block** – The block that each person is assigned to. We will use a person's location to assign them to a block.
- **SamePerson** – The target data that we are trying to predict. We will try to resolve reference on the full cross-product of people.
- **Similar** – An arbitrary similarity measure between two people. This can represent the aggregation of the similarity of several local features.

Our model contains the following rules:

$$\begin{aligned}
&\textsc{Block}(\texttt{P1},\texttt{B}) \land \textsc{Block}(\texttt{P2},\texttt{B}) \land (\texttt{P1} \neq \texttt{P2}) \land \textsc{Similar}(\texttt{P1},\texttt{P2}) && \implies \textsc{SamePerson}(\texttt{P1},\texttt{P2})\\
&\textsc{Block}(\texttt{P1},\texttt{B}) \land \textsc{Block}(\texttt{P2},\texttt{B}) \land \textsc{Block}(\texttt{P3},\texttt{B}) && \\
&\qquad \land (\texttt{P1} \neq \texttt{P3}) \land \textsc{SamePerson}(\texttt{P1},\texttt{P2}) \land \textsc{SamePerson}(\texttt{P2},\texttt{P3}) && \implies \textsc{SamePerson}(\texttt{P1},\texttt{P3})\\
&\textsc{Block}(\texttt{P1},\texttt{B}) \land \textsc{Block}(\texttt{P2},\texttt{B}) \land (\texttt{P1} \neq \texttt{P2}) \land \textsc{SamePerson}(\texttt{P1},\texttt{P2}) && \implies \textsc{SamePerson}(\texttt{P2},\texttt{P1})\\
&\textsc{Block}(\texttt{P1},\texttt{B}) \land \textsc{Block}(\texttt{P2},\texttt{B}) && \implies \neg\textsc{SamePerson}(\texttt{P2},\texttt{P1})
\end{aligned}$$

Note that the blocking is very aggressive in this model. This aggressive blocking and no overlapping blocks ensure that we are solving the same Markov random field and not a related one as discussed in section 3.1.1.

This model covers three generic types of rules that are usually utilized with entity resolution problems:

1. Local similarity. We utilize a single predicate SIMILAR as a stand-in for an aggregate of local similarity features. This rule captures what would be utilized by a machine learning method that does not utilize the relational structure of the data. When implemented without blocking, this rule will produce a number of groundings on the order of he number of entities squared.
2. Transitivity. Transitivity is a very natural property of entity resolution: if two reference are the same as a common reference, then all three references are the same. However, a transitivity rule can very easily generate enough ground rules to make a problem infeasible to solve on a single machine. When implemented without blocking, a transitivity rule will produce a number of groundings on the order of the number of entities cubed.
3. Symmetry. Symmetry rules just ensures that the order of arguments to a predicate do not matter. It the input data is carefully processed, symmetry rules may not be necessary.
4. Prior. Most SRL models will include some prior about the inferred predicate. Here we enforce a negative prior, stating that be default people are not the same. Note that blocking is enforced even on our prior.

4.1.2 Data

We start with a specified number of person references and locations. For each reference, we assign them with a uniform probability to a location. We then generate a similarity score by sampling from different Gaussian distributions depending on if the two reference come from the same location. The parameters of the different Gaussian are adjustable.

The different datasets generated and the parameters used to generate them can be seen in Table 1.

People	Locations	High Similarity Mean	High Similarity Variance	Low Similarity Mean	Low Similarity Variance
200	10	0.8	0.1	0.2	0.1
200	20	0.8	0.1	0.2	0.1
200	30	0.8	0.1	0.2	0.1
300	10	0.8	0.1	0.2	0.1
300	20	0.8	0.1	0.2	0.1
300	30	0.8	0.1	0.2	0.1
400	10	0.8	0.1	0.2	0.1
400	20	0.8	0.1	0.2	0.1
400	30	0.8	0.1	0.2	0.1
500	10	0.8	0.1	0.2	0.1
500	20	0.8	0.1	0.2	0.1
500	30	0.8	0.1	0.2	0.1
600	10	0.8	0.1	0.2	0.1
600	20	0.8	0.1	0.2	0.1
600	30	0.8	0.1	0.2	0.1

Table 1: Parameters used to generate synthetic datasets.

4.2 Bibliographic

4.2.1 Model

For the bibliographic data, our entities are publications (P) and authors (A), and our model is as follows:

Local attribute similarity

If the publication titles are similar, the publications are the same

$$\textsc{BlockPub}(\texttt{P1},\texttt{B}) \wedge \textsc{BlockPub}(\texttt{P2},\texttt{B}) \wedge \textsc{SimTitleString}(\texttt{P1},\texttt{P2}) \implies \textsc{SamePub}(\texttt{P1},\texttt{P2})$$

If the author mentions have similar names, the authors are the same

$$\textsc{BlockAuthor}(\texttt{A1},\texttt{B}) \wedge \textsc{BlockAuthor}(\texttt{A2},\texttt{B}) \wedge \textsc{SimNames}(\texttt{A1},\texttt{A2}) \implies \textsc{SameAuthor}(\texttt{A1},\texttt{A2})$$

If publications don't have similar author strings, they are not the same publication

$$\textsc{BlockPub}(\texttt{P1},\texttt{B}) \wedge \textsc{BlockPub}(\texttt{P2},\texttt{B}) \wedge \neg\textsc{SimAuthorString}(\texttt{P1},\texttt{P2}) \implies \neg\textsc{SamePub}(\texttt{P1},\texttt{P2})$$

Relational rules

If two publications are the same, the authors for the publication are the same

$$\begin{aligned}&\textsc{BlockPub}(\texttt{P1},\texttt{BP}) \wedge \textsc{BlockPub}(\texttt{P2},\texttt{BP})\\ &\quad\wedge \textsc{BlockAuthors}(\texttt{A1},\texttt{BA}) \wedge \textsc{BlockAuthors}(\texttt{A2},\texttt{BA})\\ &\quad\wedge \textsc{SamePub}(\texttt{P1},\texttt{P2}) \wedge \textsc{HasAuthor}(\texttt{P1},\texttt{A1}) \wedge \textsc{HasAuthor}(\texttt{P2},\texttt{A2})\\ &\quad\wedge \textsc{SimNames}(\texttt{A1},\texttt{A2}) \implies \textsc{SameAuthor}(\texttt{A1},\texttt{A2})\end{aligned}$$

The author co-occurrence rule: If two mentions co-occur, and one pair is known to be the same, the pair is the same if the names are similar

$$\begin{aligned}&\textsc{BlockAuthors}(\texttt{A1},\texttt{B}) \wedge \textsc{BlockAuthors}(\texttt{A2},\texttt{B})\\ &\quad\wedge \textsc{BlockAuthors}(\texttt{A3},\texttt{B}) \wedge \textsc{BlockAuthors}(\texttt{A4},\texttt{B})\\ &\quad\wedge \textsc{areCoAuthors}(\texttt{A1},\texttt{A2}) \wedge \textsc{areCoAuthors}(\texttt{A3},\texttt{A4})\\ &\quad\wedge \textsc{SameAuth}(\texttt{A1},\texttt{A3}) \wedge \textsc{SimNames}(\texttt{A2},\texttt{A4}) \implies \textsc{SameAuthor}(\texttt{A2},\texttt{A4})\end{aligned}$$

Collective rules

Transitive closure for publications and authors

$$\begin{aligned}&\textsc{BlockPub}(\texttt{P1},\texttt{B}) \wedge \textsc{BlockPub}(\texttt{P2},\texttt{B}) \wedge \textsc{BlockPub}(\texttt{P3},\texttt{B})\\ &\quad\wedge \textsc{SamePub}(\texttt{P1},\texttt{P2}) \wedge \textsc{SamePub}(\texttt{P2},\texttt{P3}) \implies \textsc{SamePub}(\texttt{P1},\texttt{P3})\end{aligned}$$

$$\begin{aligned}&\textsc{Block}(\texttt{A1},\texttt{B}) \wedge \textsc{Block}(\texttt{A2},\texttt{B}) \wedge \textsc{Block}(\texttt{A3},\texttt{B})\\ &\quad\wedge \textsc{SameAuthor}(\texttt{A1},\texttt{A2}) \wedge \textsc{SameAuthor}(\texttt{A2},\texttt{A3}) \implies \textsc{SameAuthor}(\texttt{A1},\texttt{A3})\end{aligned}$$

Priors

In the absence of evidence, two publication mentions do not correspond to the same publication, and two author mentions do not correspond to the same author.

$\textsc{BlockPub}(\texttt{P1}, \texttt{B}) \wedge \textsc{BlockPub}(\texttt{P2}, \texttt{B}) \implies \neg\textsc{SamePub}(\texttt{P1}, \texttt{P2})$

$\textsc{BlockAuthor}(\texttt{A1}, \texttt{B}) \wedge \textsc{BlockAuthor}(\texttt{A2}, \texttt{B}) \implies \neg\textsc{SameAuthor}(\texttt{A1}, \texttt{A2})$

Note that every rule has a blocking predicate that restricts the comparisons that are made in each rule. There is an additional constraint in every rule that is not mentioned in the rules above for the sake of brevity – the arguments P1 and P2, and A1 and A2 are not the same. We write this as P1 - P2, or P1 != P2 in PSL.

All of these rules are natural assumptions that model the domain, and PSL provides the necessary expressivity. Some rules need tuning. For instance, the co-occurrence rule in its current form is not very useful because of the way it is blocked. It only compares co-authors within the same block. However, we need to convert this into a rule where the pair of authors being inferred can be from different blocks. We note this for future work.

4.2.2 Data

There are several variations of the CORA dataset, and all required preprocessing for use in our experiments. We used the dataset mentioned in Singla and Domingos (2006). Notably, this dataset did not provide the ground truth for all authors. After preprocessing and semi-supervised clustering to get all the author ground truth, our dataset consisted of 1295 publication mentions of 134 distinct publications, and 3524 author mentions of 51 distinct authors. Initially, we tried to perform inference on the entire dataset, but we defer this for future work, since it would take several days to solve.

We sampled 300 publication mentions randomly and used this for our experiments. This subsampled dataset contains 92 unique publications and 43 unique authors from 840 author mentions.

Large problems do not fit on single node machines on account of the memory requirements for grounding rules. Under the blocking scheme we performed our experiments with, even with under 75% of the dataset, we expect about 15 million ground rules. With the complete dataset, we tried and were not able to fit this on the largest server available to us with 384GB of RAM. To overcome this single node memory limitation, we propose that the grounding of rules be distributed across several nodes. In an entity resolution problem, the need for blocking to reduce the number of comparisons naturally offers a partitioning scheme. Under this scheme, nodes are assigned blocks and each node only grounds the rules corresponding to the blocks that it is assigned, thereby reducing the number of ground rules per node.

4.2.3 Blocking methods

Since we have two types of entities to resolve – publications and authors – we have different blocking schemes for each. We only discuss variations of blocking for author mentions, noting that publication mentions were blocked based on the ‘year’ field, i.e., two publications belong to the same block if their ‘year’ field matches.

Not all blocking schemes are equal, especially in the context of their use in partitioning data. In our naïve author blocking scheme BM4 (elaborated below), we create a set s_i of the first character of each token in an author’s mention m_i. Each such set is used as a blocking key. A mention is assigned to a block if its set of first characters are a subset of or equal to the blocking key. Then, a mention m_{i_1} and a mention m_{i_2} are in the same block if $s_{i_1} \cap s_{i_2} \neq \emptyset$. This results in 58 blocks, with a mean of 23.47 mentions, and a standard deviation of 39.05. The largest block contained 162 author mentions.

Considering the full dataset for a moment to truly understand the scale, we saw 80 blocks with BM4, with a mean of 86 mentions, and a standard deviation of 156. Five blocks had over 500 mention. Since a block is the minimum unit of data partitioning, the problem of insufficient memory manifests when these 500+ mention blocks are assigned to a machine, especially with the transitive rule. Hence we prefer blocking schemes that result in smaller block sizes.

We started with four naïve blocking methods, described below. First, some notation:

- C_3 is the set of upto three characters from each token in the mention.

Method	Compression	Recall	Number of blocks	(μ, σ, max) mentions per block
BM1	0.9056	0.6922	95	(15.38, 22, 125)
BM2	0.7857	0.9958	45	(37.42, 45.16, 185)
BM3	0.8432	0.9328	121	(15.26, 26.49, 159)
BM4	0.8333	0.9947	58	(23.47, 39.05, 162)
BM5	0.9607	0.2110	1389	(3.16, 3.89, 63)
BM6	0.9553	0.2423	1389	(3.93, 4.35, 63)
BM7	0.9262	0.4214	1389	(6.45, 7.14, 63)

Table 2: Comparison of blocking techniques applied to 840 mentions of 43 unique authors

- I is the set of the first character from each token in the mention.

Two mentions are in the same block if:

- BM1: The intersection of their C_3 has at least two elements
- BM2: The intersection of their C_3 has at least one element
- BM3: The intersection of their C_3 has at least one 3 character element
- BM4: The I of one mention is a subset of the other mention

In our goal for more efficient distribution, and to exploit the relational nature of PSL, we implemented a two-level blocking scheme with a distribution parameter η. The first level of blocks are based on string equality. Two mentions are in the same block if they match exactly. This results in 189 block keys (from 840 mentions), $bk1_1, bk1_2, ...bk1_{189}$. The second level of blocking creates a blocking key $bk2_j$ using the BM4 criterion, conceptually operating on the block keys $bk1_i$ rather than the mentions. If $bk1_{i_1}$ and $bk1_{i_2}$ have the same $bk2_j$, a small percentage η of mentions from each $bk1_i$ are added under the block.

η is a parameter that allows us to control the size of the blocks at level two, and also control the recall and compression as measured in a non-hierarchical setting. Our hypothesis is that even with a small percentage of η, using a relational model will enable us to recover the entity matches across the $bk2$ second level. We experimented with the following etas:

- BM5: two-level blocking with η = 0.1
- BM6: two-level blocking with η = 0.2
- BM7: two-level blocking with η = 0.5

Our intuition is that this form of blocking is closely related to lifted inference. Ideally, rather than grounding all triples for transitivity, our goal was to perform transitivity at the level of the exact match blocks. This implementation is a matter of future work. For now, we write a rule designed to take advantage of this multi-level blocking:

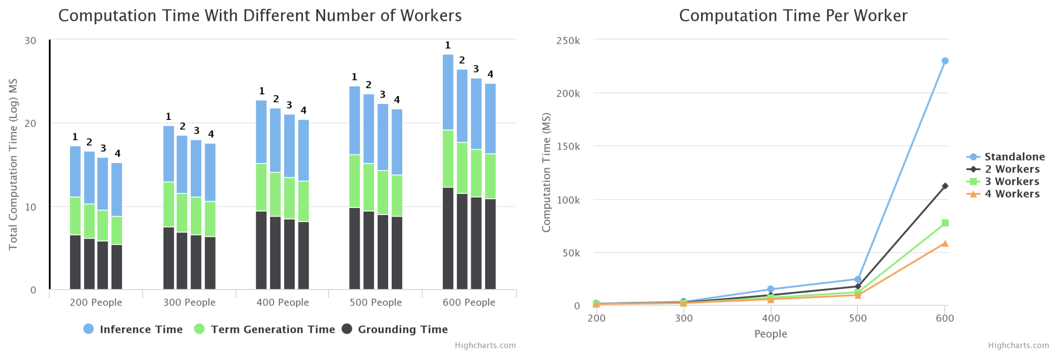
$$\begin{aligned}&\textsc{Block}(\texttt{A1},\texttt{B1}) \wedge \textsc{Block}(\texttt{A2},\texttt{B1})\\ &\quad \wedge \textsc{Block}(\texttt{A2},\texttt{B2}) \wedge \textsc{Block}(\texttt{A3},\texttt{B2})\\ &\quad \wedge \textsc{SameAuthor}(\texttt{A1},\texttt{A2}) \wedge \textsc{SameAuthor}(\texttt{A2},\texttt{A3}) \implies \textsc{SameAuthor}(\texttt{A1},\texttt{A3})\end{aligned}$$

This rule forces a comparison across blocks that have an overlapping element. We call this rule X in the results section.

We also implemented following more advanced blocking methods: Adaptive blocking (Bilenko et al. (2006)) and Canopies (McCallum et al. (2000)). Evaluation of the blocks output by these schemes are part of our proposed future work. Table 2 compares the various blocking methods we implemented.

4.2.4 Similarity measure

The similarity metric chosen plays a vital role in the results, as we observed in one of our experiments. We started with using Jaro-Winkler distance for both, publication titles and author mentions. However, we saw poor precision (0.1871) with our model. However, changing to cosine similarity on TF-IDF vectorized publication titles improved the precision to 0.9589, a jump with no other changes to the



(a) Broken Down Times

(b) Computation Time

Figure 1: Runtimes for different number of workers.

	Auth Prec	Auth Recall	Pub Prec	Pub Recall
No Trans, BM4	0.7662	0.7888	0.9855	0.8718
Trans, BM4	**0.7913**	**0.8907**	0.9855	0.8718
No Trans, BM5	0.6186	0.0866	0.9855	0.8718
Rule X, BM5	0.4042	0.1122	0.9855	0.8718

Table 3: Inference results with the CORA dataset

model. This improvement did come at the cost of reduced recall, which went down from 0.8579 to 0.7955. We refrain from further improving our model, since our goal for this project is scalability. We do however, intend to tune the model and formally learn weights in the future.

5 Results

5.1 Distribution

The purpose of this experiment is to examine the effect of distribution on runtime and memory performance. The accuracy, recall, and precision of all runs are within 0.03 of each other.

5.1.1 Runtime

In general, we see across the board reduction in computation times. Figure 1a shows the time spent on grounding, term generation, and inference for various configurations (all with 20 blocks). Notice the log scale. Occasionally we see that with fewer number of people, inference on more workers taking longer than with fewer workers because of the network overhead.

Figure 1b shows the aggregated runtime in a linear scale. Here we can truly see the advantage of distribution as the size of the problem grows.

Table 4 in appendix B shows the full results.

5.1.2 Number of Ground Rules

As expected, we see the number of ground rules (optimization terms) as well as the number of global and local variables drop as we distribute the problem across several workers.

Table 5 in appendix B shows the full results.

5.2 Bibliographic

Results with the bibliographic data subset are shown in Figure 4 and Table 3. To recap, BM4 is the blocking method that uses the first character of each token in the author mention, and BM5 is the two-level blocking method with $\eta = 0.1$.

(a) Local Variables (b) Global Variables

Figure 2: The mean number of variables on a worker.

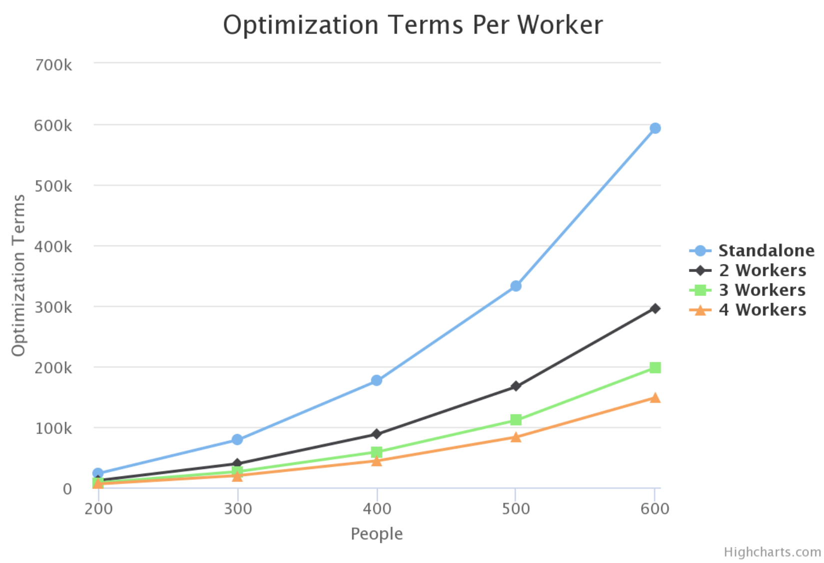


Figure 3: The mean number of optimization terms (ground rules) on a worker.

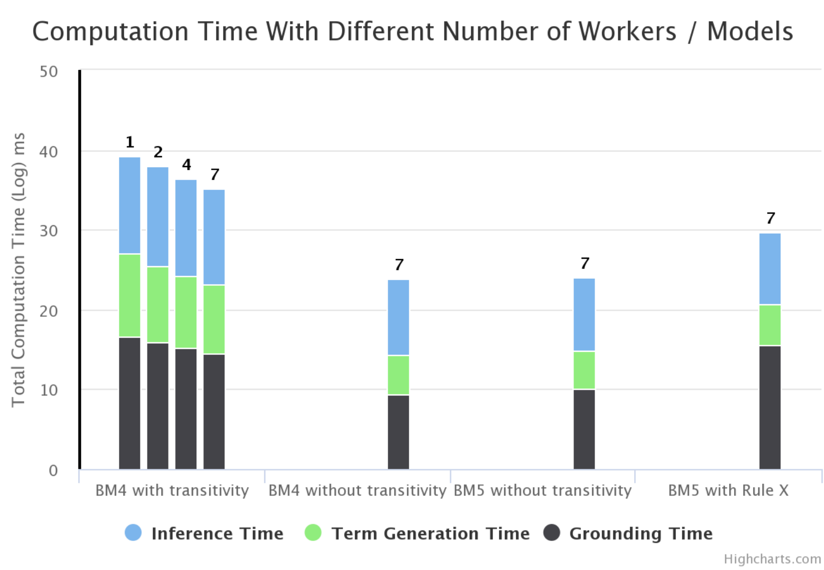


Figure 4: Comparison of execution times with variation in blocking methods, and transitivity rules.

We see from the table that transitivity certainly helps, proving the usefulness of the relational rule of transitivity, and justifying the cubic space complexity incurred. Since grounding takes a substantial amount of time, this translates to an increase in time complexity as well. As we see in Figure 4 in the 'BM4 with transitivity' category, a distributed implementation helps us deal with this by distributing the grounding across nodes, leading to improved grounding and overall execution times.

The BM4 with transitivity PSL model has 15.2 million ground rules. While a single node took 277 minutes to ground, grounding took place in 34 minutes, with seven nodes.

The hierarchical blocking method BM5 performs poorly. It buys us no precision, recall, nor even improved grounding times when coupled with rule X. However, this is expected since it will need a strong non-blocking rule that will propagate transitivity across the second level of blocks. It is a matter of surprise, however, that the recall after inference is poorer than what recall is offered at the level of blocking.

6 Related Work

6.1 Entity resolution

Statistical relational techniques have been previously applied to entity resolution. Notably, Singla and Domingos (2006) address Entity Resolution using Markov Logic Networks. Bhattacharya (2006) predates PSL, contains important work about formulating ER as a collective inference problem. It compares several similarity and neighbourhood similarity metrics, and introduces a relational clustering algorithm. For a more recent treatment, albeit within the context of knowledge graph ER, Pujara and Getoor (2016) describes common modeling patterns and rules.

Köpcke and Rahm (2010) provide a nice overview of several entity resolution solutions. We use the same bibliographic datasets that they use enabling a comparison with their metrics.

Distributed scaling has been successfully implemented in the past in Pujara (2016) for knowledge graph identification (KGI), where a knowledge graph was partitioned across multiple machines. In the domain of ER, just as in the domain of KGI, the challenge lies in partitioning data without losing relationships in the graphical model.

6.2 Parallelizing Entity Resolution

There are several papers that specifically talk about distributing or parallelizing Entity Resolution problems. Benjelloun et al. (2007) and Kawai et al. (2006) presents a family of algorithms for distributing/parallelizing the ER workload across multiple processors. This is a family of algorithms because they treat the matching and record merging functions (as well as the distributing functions) as black boxes, where any relevant function of choice can be substituted. Efthymiou et al. (2017) introduces algorithms for Meta-blocking that use the Map Reduce framework. Meta-blocking is used to clean the overlapping blocks from unnecessary comparisons. Dal Bianco et al. (2011)'s MD-approach combines an efficient blocking method with a robust data parallel programming model for a salable deduplication solution. Malhotra et al. (2014) compare two distribution approaches that they call bucket-centric and record-centric with a focus on load balancing. Kirsten et al. (2010) propose different strategies to partition the input data and generate multiple match tasks that can be independently executed. Kim and Lee (2007) study scenarios where the collections being compared/merged are clean, only one is clean, and both are dirty to exploit interplay between match and merge to achieve parallelization. Rastogi et al. (2011) propose a principled framework to scale any generic entity matching algorithm by running multiple instances of the EM algorithm on small neighborhoods of the data and passing messages across neighborhoods to construct a global solution.

7 Discussion

Entity Resolution is a large problem that can quickly become unmanageable. A standard ER solution will grow to the order of the number of entities squared. In the collective inference setting, the addition of a transitivity rule will cause the problem to grow to the order of the number of entities cubed. To combat this growth, we have shown that blocking and distributing the optimization problem can be utilized to reduce the memory burden on a single machine and solve problems more quickly.

We use a greedy selection of blocks (based on the size of elements in a block) to assign to nodes. In cases where the workers used are heterogeneous (as in our case with the bibliography ER experiments) there is room for improvement by assigning bigger blocks to more powerful machines. In all cases, we saw that the bottleneck was the grounding time on the least powerful server.

We also saw that there is merit in tightly coupling the blocking criterion with the distribution scheme, especially when the transitivity rule is used. Since the complexity of grounding is effectively cubic in the size of the block when using transitivity, smaller blocks can significantly reduce the total execution time. We noticed that the blocks were unevenly sized under the BM4 method. We hypothesize that a two step inference approach where the first step resolves the easier to resolve mentions to their entities followed by a round of inference on these 'lifted' resolved entities may be a viable approach to solving the problem, and will be explored in future work. Wick et al. (2009) have addressed this problem in the past.

Overall, we successfully implemented a distributed implementation of PSL leveraging blocking for partitioning the data, making problems that hitherto did not fit on a single machine approachable, and the results also show a significant improvement in inference time, as grounding time reduces linearly with the number of machines added.

Appendices

A Additional Diagrams

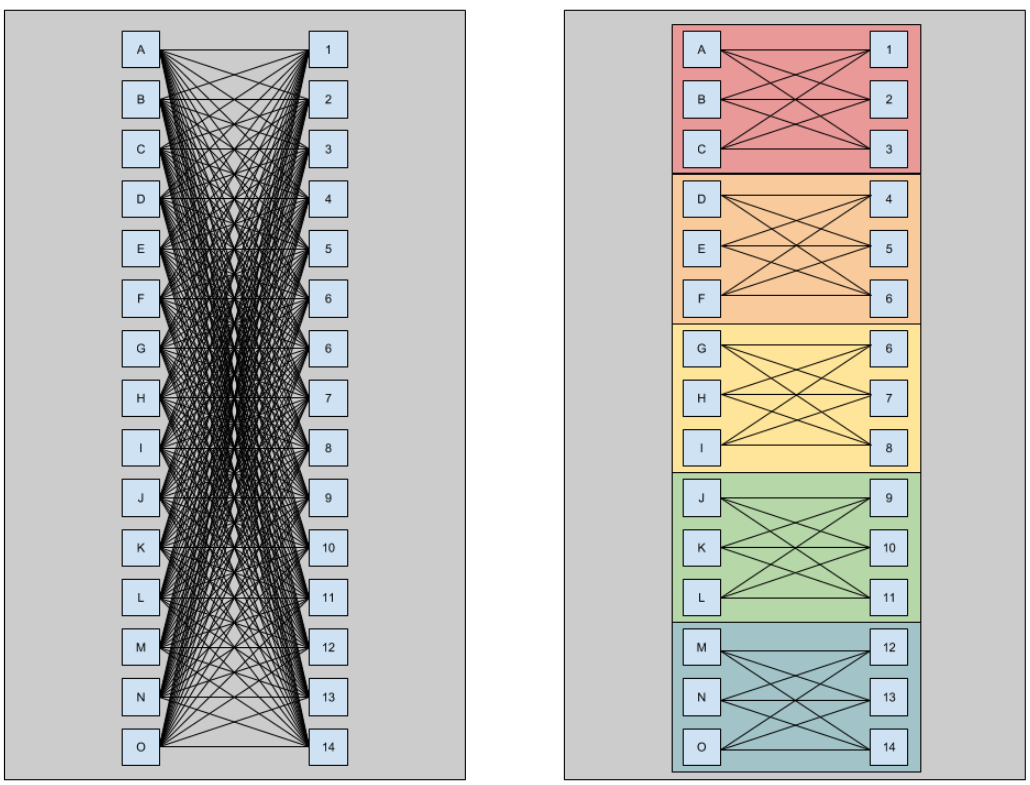


Figure 5: Blocking reduces the number of comparisons from 196 on the left to 45 on the right.

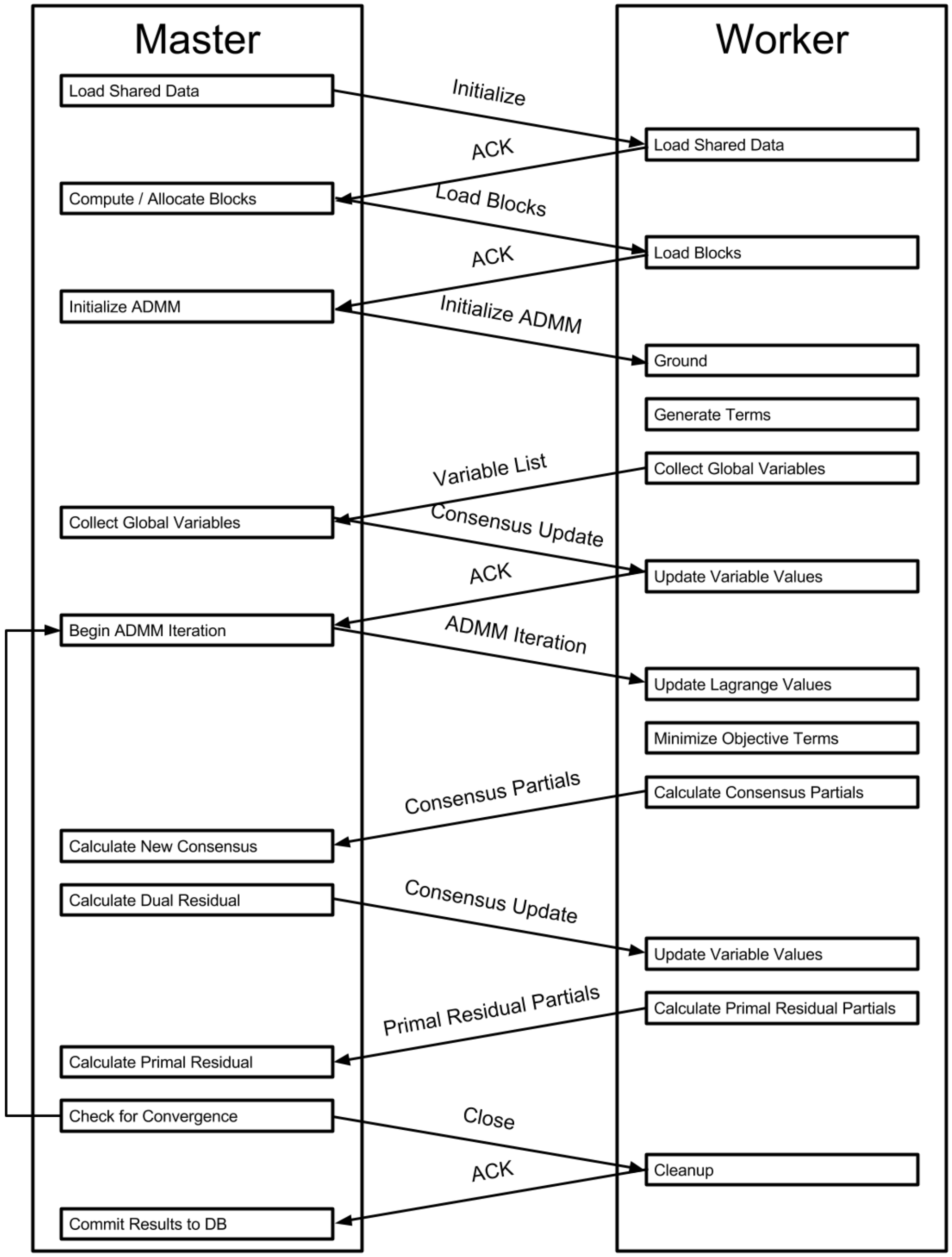


Figure 6: The control flow between the master and worker nodes in the distributed ADMM implementation.

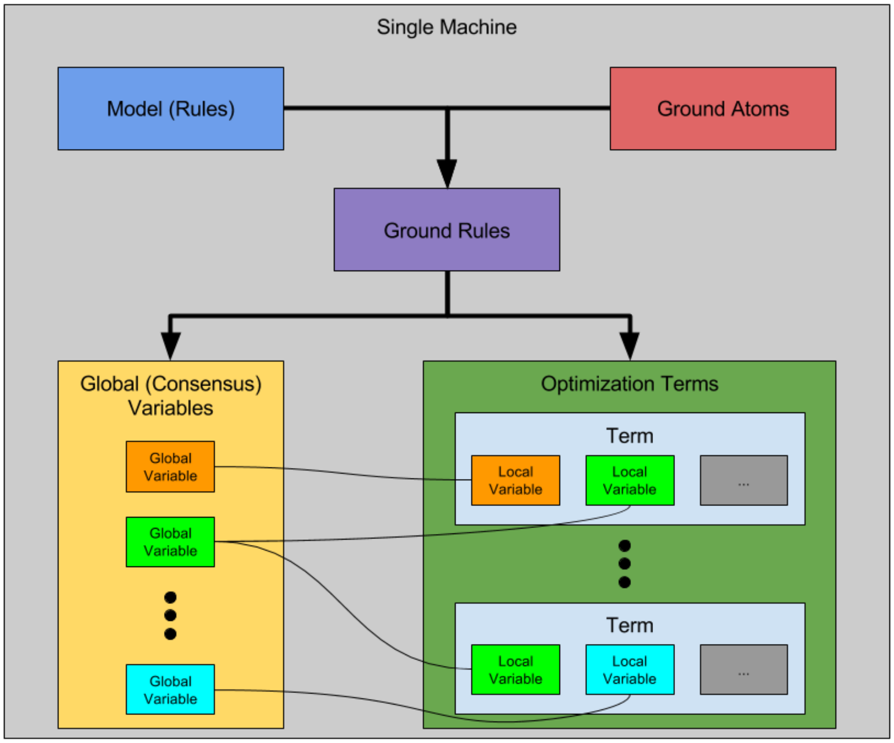


Figure 7: The location of critical pieces of data in our standalone ADMM implementation.

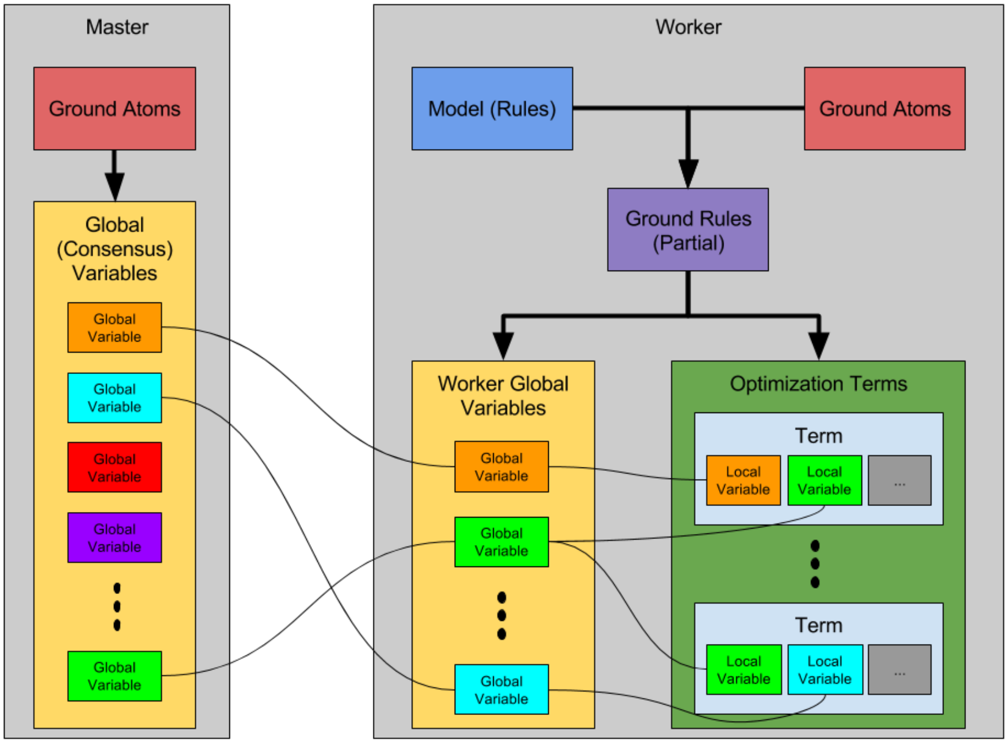


Figure 8: The location of critical pieces of data in our distributed ADMM implementation.

B Full Results

Table 4 shows full runtime results on synthetic data. Table 5 shows full term and variable results on synthetic data.

People	Blocks	Workers	Grounding (ms)	Term Generation (ms)	Inference (ms)	Computation (ms)
200	10	1	1783	182	1023	2988
200	20	1	733	95	449	1277
200	30	1	473	47	276	796
300	10	1	5928	444	3769	10141
300	20	1	1815	218	895	2928
300	30	1	1029	121	495	1645
400	10	1	21983	1107	8214	31304
400	20	1	12288	301	2196	14785
400	30	1	8324	229	906	9459
500	10	1	66635	2111	18570	87316
500	20	1	19828	547	4080	24455
500	30	1	14391	289	1895	16575
600	10	1	493776	4112	41014	538902
600	20	1	219647	944	9287	229878
600	30	1	154071	448	3073	157592
200	10	2	928	122	1445	2495
200	20	2	465	64	587	1116
200	30	2	246	38	502	786
300	10	2	2572	288	3694	6554
300	20	2	976	106	1094	2176
300	30	2	576	74	740	1390
400	10	2	11733	497	8793	21023
400	20	2	6771	190	2307	9268
400	30	2	5892	111	1271	7274
500	10	2	22534	1008	19127	42669
500	20	2	12909	300	4298	17507
500	30	2	10078	149	2335	12562
600	10	2	229961	1851	27328	259140
600	20	2	104648	471	6867	111986
600	30	2	73800	262	3560	77622
200	10	3	726	97	1278	2101
200	20	3	342	39	604	985
200	30	3	191	23	474	688
300	10	3	1921	187	2725	4833
300	20	3	713	92	971	1776
300	30	3	398	52	720	1170
400	10	3	7566	328	6886	14780
400	20	3	4661	157	2061	6879
400	30	3	4030	97	1107	5234
500	10	3	14332	812	12526	27670
500	20	3	8394	188	3413	11995
500	30	3	6860	141	1738	8739
600	10	3	137243	1108	19364	157715
600	20	3	71582	304	4998	76884
600	30	3	48313	170	2556	51039
200	10	4	567	76	1527	2170
200	20	4	226	30	623	879
200	30	4	156	31	458	645
300	10	4	1452	160	2817	4429
300	20	4	569	72	1125	1766
300	30	4	338	36	702	1076
400	10	4	5932	285	10056	16273
400	20	4	3531	126	1717	5374
400	30	4	3040	73	1138	4251
500	10	4	11393	526	18595	30514
500	20	4	6351	155	2778	9284
500	30	4	5240	116	1901	7257
600	10	4	102056	1144	28093	131293
600	20	4	53408	234	4685	58327
600	30	4	37323	150	2534	40007

Table 4: Full runtime results.

People	Nodes	Blocks	Node 1 Terms	Node 1 Local	Node 1 Global	Node 2 Terms	Node 2 Local	Node 2 Global	Node 3 Terms	Node 3 Local	Node 3 Global	Node 4 Terms	Node 4 Local	Node 4 Global
200	1	10	86191	239089	3906	-	-	-	-	-	-	-	-	-
200	1	20	23516	60968	1920	-	-	-	-	-	-	-	-	-
200	1	30	12916	32134	1326	-	-	-	-	-	-	-	-	-
300	1	10	290256	826202	8930	-	-	-	-	-	-	-	-	-
300	1	20	78764	214046	4458	-	-	-	-	-	-	-	-	-
300	1	30	36382	94594	2916	-	-	-	-	-	-	-	-	-
400	1	10	676125	1949021	15908	-	-	-	-	-	-	-	-	-
400	1	20	176031	488853	7866	-	-	-	-	-	-	-	-	-
400	1	30	85925	231279	5314	-	-	-	-	-	-	-	-	-
500	1	10	1306446	3795226	24880	-	-	-	-	-	-	-	-	-
500	1	20	332686	936826	12276	-	-	-	-	-	-	-	-	-
500	1	30	158484	434366	8234	-	-	-	-	-	-	-	-	-
600	1	10	2305962	6737342	36200	-	-	-	-	-	-	-	-	-
600	1	20	592873	1688919	17978	-	-	-	-	-	-	-	-	-
600	1	30	265055	736187	11820	-	-	-	-	-	-	-	-	-
200	2	10	50097	139511	2162	36094	99578	1744	-	-	-	-	-	-
200	2	20	10843	27959	916	12673	33009	1004	-	-	-	-	-	-
200	2	30	5607	13647	636	7309	18487	690	-	-	-	-	-	-
300	2	10	150425	429693	4324	139831	396509	4606	-	-	-	-	-	-
300	2	20	39962	108636	2254	38802	105410	2204	-	-	-	-	-	-
300	2	30	15027	38427	1332	21355	56167	1584	-	-	-	-	-	-
400	2	10	354004	1023308	7756	322121	925713	8152	-	-	-	-	-	-
400	2	20	85240	236410	3870	90791	252443	3996	-	-	-	-	-	-
400	2	30	42399	113797	2686	43526	117482	2628	-	-	-	-	-	-
500	2	10	864840	2518642	15214	441606	1276584	9666	-	-	-	-	-	-
500	2	20	160173	450775	5962	172513	486051	6314	-	-	-	-	-	-
500	2	30	77323	212085	3986	81161	222281	4248	-	-	-	-	-	-
600	2	10	1267273	3711333	18140	1038689	3026009	18060	-	-	-	-	-	-
600	2	20	290480	826592	8988	302393	862327	8990	-	-	-	-	-	-
600	2	30	141302	392924	6210	123753	343263	5610	-	-	-	-	-	-
200	3	10	31036	85784	1468	22111	60983	1072	33044	92322	1366	-	-	-
200	3	20	6802	17410	600	7407	19077	630	9307	24481	690	-	-	-
200	3	30	2849	6779	354	4494	11144	470	5573	14211	502	-	-	-
300	3	10	84783	240969	2682	100365	285125	3200	105108	300108	3048	-	-	-
300	3	20	22145	59869	1316	24284	65852	1404	32335	88325	1738	-	-	-
300	3	30	14647	38381	1114	9152	23354	822	12583	32859	980	-	-	-
400	3	10	235473	679703	5354	213699	616451	4940	226953	652867	5614	-	-	-
400	3	20	51792	143012	2480	48455	133739	2328	75784	212102	3058	-	-	-
400	3	30	31727	85797	1882	22800	60962	1490	31398	84520	1942	-	-	-
500	3	10	469009	1364551	8514	417329	1213207	7778	420108	1217468	8588	-	-	-
500	3	20	96085	269471	3766	136214	385836	4570	100387	281519	3940	-	-	-
500	3	30	57221	157459	2846	47659	130301	2542	53604	146606	2846	-	-	-
600	3	10	810841	2371249	12288	718727	2094819	12304	776394	2271274	11608	-	-	-
600	3	20	221175	630883	6544	200276	571484	5880	171422	486552	5554	-	-	-
600	3	30	86401	240087	3830	76070	210504	3550	102584	285596	4440	-	-	-
200	4	10	20412	56218	1006	19864	55186	882	16230	44392	862	29685	83293	1156
200	4	20	4408	11128	420	5458	14088	458	6536	17076	508	7114	18676	534
200	4	30	2339	5549	294	1877	4433	240	4342	11090	388	4358	11062	404
300	4	10	53933	153113	1740	100055	285373	2966	48706	137004	1826	87562	250712	2398
300	4	20	22305	60813	1224	19856	53836	1148	20526	55870	1144	16077	43527	942
300	4	30	10506	27640	778	7035	17991	624	10131	26569	766	8710	22394	748
400	4	10	188903	546465	4054	124917	357465	3468	133905	385895	3170	228400	659196	5216
400	4	20	50291	140279	2124	42403	117431	1960	38123	105415	1796	45214	125728	1986
400	4	30	21182	57066	1300	19991	53767	1244	20243	54385	1274	24509	66061	1496
500	4	10	371596	1082916	6392	271082	783902	5880	276186	802758	5172	387582	1125650	7436
500	4	20	89757	253171	3226	80881	227619	3014	70454	197594	2760	91594	258442	3276
500	4	30	43394	119482	2144	28816	77914	1710	42734	117492	2146	43540	119478	2234
600	4	10	784824	2301896	10544	412348	1203408	6740	437548	1272216	8108	671242	1959822	10808
600	4	20	129487	367757	4150	163772	467810	4710	143831	409163	4476	155783	444189	4642
600	4	30	72565	202319	3082	50102	137778	2512	70466	196448	2994	71922	199642	3232

Table 5: Full term and variables results.

References

Bach, S. H., Broecheler, M., Huang, B., and Getoor, L. (2015). Hinge-loss markov random fields and probabilistic soft logic. *arXiv preprint arXiv:1505.04406*.

Benjelloun, O., Garcia-Molina, H., Gong, H., Kawai, H., Larson, T. E., Menestrina, D., and Thavisomboon, S. (2007). D-swoosh: A family of algorithms for generic, distributed entity resolution. In *Distributed Computing Systems, 2007. ICDCS'07. 27th International Conference on*, pages 37–37. IEEE.

Bhattacharya, I. (2006). *Collective Entity Resolution In Relational Data*. PhD thesis, University of Maryland, College Park.

Bhattacharya, I. and Getoor, L. (2007). Collective entity resolution in relational data. *ACM Trans. Knowl. Discov. Data*, 1(1).

Bilenko, M., Kamath, B., and Mooney, R. J. (2006). Adaptive blocking: Learning to scale up record linkage. In *Data Mining, 2006. ICDM'06. Sixth International Conference on*, pages 87–96. IEEE.

Boyd, S., Parikh, N., Chu, E., Peleato, B., and Eckstein, J. (2011). Distributed optimization and statistical learning via the alternating direction method of multipliers. *Foundations and Trends® in Machine Learning*, 3(1):1–122.

Dal Bianco, G., Galante, R., and Heuser, C. A. (2011). A fast approach for parallel deduplication on multicore processors. In *Proceedings of the 2011 ACM Symposium on Applied Computing*, pages 1027–1032. ACM.

Efthymiou, V., Papadakis, G., Papastefanatos, G., Stefanidis, K., and Palpanas, T. (2017). Parallel meta-blocking for scaling entity resolution over big heterogeneous data. *Information Systems*, 65:137–157.

Gabay, D. and Mercier, B. (1976). A dual algorithm for the solution of nonlinear variational problems via finite element approximation. *Computers & Mathematics with Applications*, 2(1):17–40.

Glowinski, R. and Marroco, A. (1975). Sur l'approximation, par éléments finis d'ordre un, et la résolution, par pénalisation-dualité d'une classe de problèmes de dirichlet non linéaires. *Revue française d'automatique, informatique, recherche opérationnelle. Analyse numérique*, 9(2):41–76.

Jaro, M. A. (1989). Advances in record-linkage methodology as applied to matching the 1985 census of tampa, florida. *Journal of the American Statistical Association*, 84(406):414–420.

Kawai, H., Garcia-Molina, H., Benjelloun, O., Menestrina, D., Whang, E., and Gong, H. (2006). P-swoosh: Parallel algorithm for generic entity resolution. Technical report, Stanford.

Kim, H.-s. and Lee, D. (2007). Parallel linkage. In *Proceedings of the sixteenth ACM conference on Conference on information and knowledge management*, pages 283–292. ACM.

Kirsten, T., Kolb, L., Hartung, M., Groß, A., Köpcke, H., and Rahm, E. (2010). Data partitioning for parallel entity matching. *arXiv preprint arXiv:1006.5309*.

Köpcke, H. and Rahm, E. (2010). Frameworks for entity matching: A comparison. *Data & Knowledge Engineering*, 69(2):197–210.

Malhotra, P., Agarwal, P., and Shroff, G. (2014). Graph-parallel entity resolution using lsh & imm. In *EDBT/ICDT Workshops*, pages 41–49.

McCallum, A., Nigam, K., and Ungar, L. H. (2000). Efficient clustering of high-dimensional data sets with application to reference matching. In *Proceedings of the sixth ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 169–178. ACM.

Newcombe, H. B., Kennedy, J. M., Axford, S. J., and James, A. P. (1959). Automatic linkage of vital records. *Science*, 130(3381):954–959.

Pujara, J. (2016). *Probabilistic Models for Scalable Knowledge Graph Construction*. PhD thesis, University of Maryland, College Park.

Pujara, J. and Getoor, L. (2016). Generic statistical relational entity resolution in knowledge graphs. In *Sixth International Workshop on Statistical Relational AI*. IJCAI 2016. On arXiv: https://arxiv.org/abs/1607.00992.

Rastogi, V., Dalvi, N., and Garofalakis, M. (2011). Large-scale collective entity matching. *Proceedings of the VLDB Endowment*, 4(4):208–218.

Singla, P. and Domingos, P. (2006). Entity resolution with markov logic. In *Data Mining, 2006. ICDM'06. Sixth International Conference on*, pages 572–582. IEEE.

Whang, S. E., Menestrina, D., Koutrika, G., Theobald, M., and Garcia-Molina, H. (2009). Entity resolution with iterative blocking. In *Proceedings of the 2009 ACM SIGMOD International Conference on Management of data*, pages 219–232. ACM.

Wick, M., Culotta, A., Rohanimanesh, K., and McCallum, A. (2009). An entity based model for coreference resolution. In *Proceedings of the 2009 SIAM International Conference on Data Mining*, pages 365–376. SIAM.